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Coverage Path Planning for Mapping of Underwater Structures

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***Abstract*—This paper addresses the problem of the coverage path planning in a 3D environment for surveying underwater structures. We propose to use the navigation strategy that a human diver will execute when circumnavigating around a region of interest, in particular when collecting data from a shipwreck. In contrast to the previous methods in the literature, we are aiming to perform coverage in completely unknown environment with some initial prior information. Our proposed method uses convolutional neural networks to learn the control commands based on the visual input. Preliminary results and a detailed overview of the proposed method are discussed.**

***Index Terms*—underwater navigation, path planning, coverage, autonomous system**

I. Introduction

When considering the coverage problem in an underwater environment the main challenge that arises is that we have to deal with three dimensions; see 8. The coverage path planning problem's complexity exponentially increases when moving from two to three dimensions. In addition, the underwater environment presents novel challenges both from the coverage and the navigation perspective. Dynamics of the water [1] and visibility constraints contribute to instability, drifting, and error in localization of an autonomous underwater vehicle (AUV); for details on the challenges of underwater sensing please refer to the comparison studies in [2]–[4].

Historical shipwrecks tell an important part of history and at the same time have a special allure for most humans, as exemplified by the plethora of movies and artworks of the Titanic; see, e.g., [5] for the visual mapping of the Titanic. Shipwrecks are also one of the top scuba diving attractions all over the world. The historical shipwrecks are deteriorating due to warm, salt water; human interference; and extreme weather (frequent tropical storms). Reconstructing accurate models of these sites will be extremely valuable not only for the historical study of the shipwrecks, but also for monitoring subsequent deterioration [6], [7]; see 2(a) for the different floors of a shipwreck exposed after a partial collapse. Currently, limited mapping efforts are performed by divers who take measurements manually using a grid and measuring tape, or using hand-held sensors [8] – a slow and sometimes dangerous task; see 2(b) for a diver collecting data, manually,

Fig. 1: Front Side View of a Shipwreck

to be used in training the navigation model. While acoustic sensing (SONAR) is common, the resulting maps do not contain the details vision can provide. The focus of this paper is to enable the autonomous operation of light-weight robots near underwater wrecks in order to collect data for creating photo-realistic maps and volumetric 3-D models. Vision has been utilized successfully to map underwater structures [9] or even underwater caves [10].

In order to perform coverage of underwater structures traditionally precise state estimation is required. But even with ideal state estimation, performing a coverage in an unknown environment exposes new and very different challenges. In this work we present an approach of vision based coverage that uses human diver knowledge on how to circumnavigate an underwater structure, e.g. a shipwreck, to perform complete coverage. In contrast to the works presented in the literature on 3D coverage [11] this work is solely based on vision and does not rely on state estimation neither requires a map of the environment for the navigation. The paper is structured as follows. First in Section II we will discuss the related work and highlight challenges that each work is facing. Following Section III the formal problem definition along with proposed method are outlined. In Section IV the preliminary results

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(a)

(b)

Fig. 2: (a) The different levels of the Stavronikita shipwreck, Barbados, after a partial collapse. (b) Diver collecting visual data for training at the Pamir shipwreck, Barbados.

are reported. Finally Section V concludes with discussions on lessons learned and how this work will progress.

II. Related Work

Even though the 3D coverage problem is known to be intractable, some approaches have been proposed and shown to have a feasible solutions both with single and multiple robots using octomaps [12], [13], some solutions have been used for ensuring even distribution of spray paint in automotive industry [14]. Another work has addressed also the coverage in unknown environment using similar to frontier-based approach [15].

Peng et al. [16] addressed the problem by representing an area through well defined 2.5D features and thus reducing the complexity of structure-dependency of the 3D coverage. The coverage problem is designed for an aerial vehicle with canonical field of view that can rotate around a fixed point with three degrees of freedom.

Similar to Palomeras et el. [17] Bircher et al. [18] combine the problem of covering an unknown environment with the given structure by sampling random next-best views in the area. It is an extension of their previous work [19] that builds a tree of next-best views and selects the best branch which is qualified by the size of unexplored area.

The coverage problem has been studied also for underwater environments and has a significant environmental and archaeological importance. Number of works presented seabed and underwater coverage path planning methods with Autonomous Surface Vehicles and Autonomous Underwater Vehicles [20], [21]. Behavior-based control of an underwater vehicle for coral-reef inspection was proposed by [22]. The behavior selection is implemented using both fuzzy logic and utility fusion. The behaviors ensure collision avoidance, proper distance from the reef and rope following or target following actions.

To ensure complete coverage without overlaps Galceran et al. [23] suggest segmenting the environment based on similar depths. Each of these segments then is considered as an individual planning problem. The proposed algorithm extends cellular decomposition performing 2.5D coverage by traveling on constant depth from the surface. This work has been extended to take also into account the state estimation uncertainty and perform replanning [24]. These works rely on the existence of prior information about the environment and they operate on the 2.5D space.

When the environment is unknown Vidal et al. [25] propose a next-best view approach but it is significantly constrained by the certainty of the state estimation. To overcome the complexity of 3D exploration, simplified formulation of the problem is considered, such as 2D mapping of underwater structure [26]. In this work authors use view planner and frontier-based strategies. The environment is represented as a quadtree occupancy map, and it is also used to generate viewpoints for the exploration.

The 3D coverage also has been shown to have wide range of applications for mapping historical artefacts and structures in underwater environments [27]. Most of the presented works either assume reliable localization or some type of prior information about the environment. Work by Manderson et al. [28] has been addressing this issue by proposing a vision based navigation in an unknown environment for coral reef coverage. The latter approach is limited by the simple structure and the type of the training data. More recent work [29] has incorporated path planning in conjunction with obstacle avoidance and bias towards areas with corals.

III. Proposed Approach

We are assuming the robot is controlled without tether, has six degrees of freedom from which controllable are yaw, pitch, roll, up and down and forward. Robot's location is given by Euclidean coordinates $\{x, y, z, \psi, \phi, \omega\}$. There is no prior information about the environment and it is deployed in a 3D-bounded area of interest $\mathcal{E} \subset \mathbb{R}^3$. The robot follows a path π that will result in the sequence of $V = \{f_1, f_2, ..., f_3\}$ stereo video frames, where f_i is the $i-th$ image frame. The objective is to ensure that π is obstacle free and that the 3D reconstruction resulted from V is covering the entire surface of the $\mathcal{E}$ object.

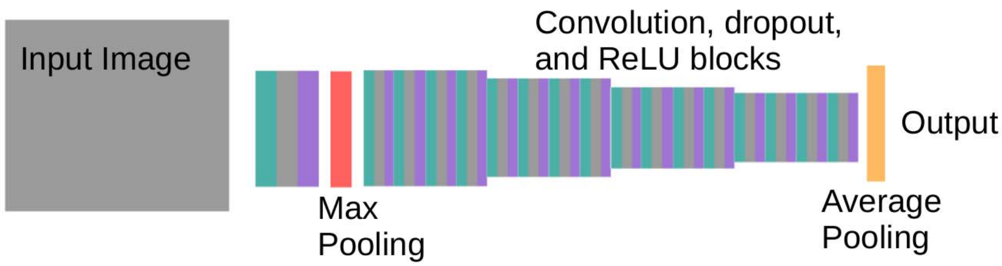
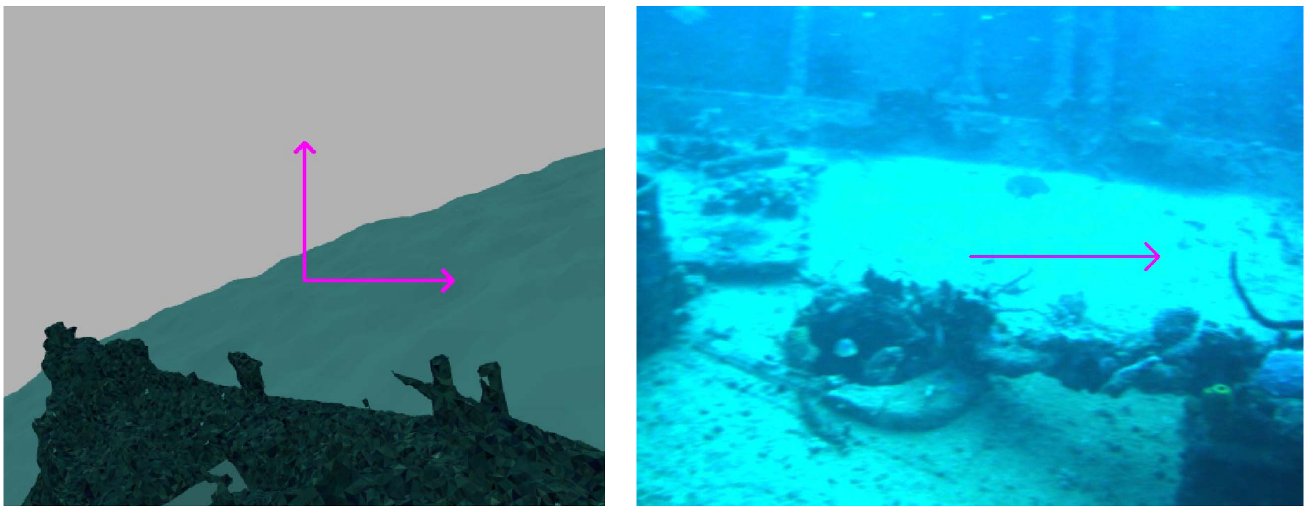


Fig. 3: The overview of Neural Network Architecture



(a) (b)

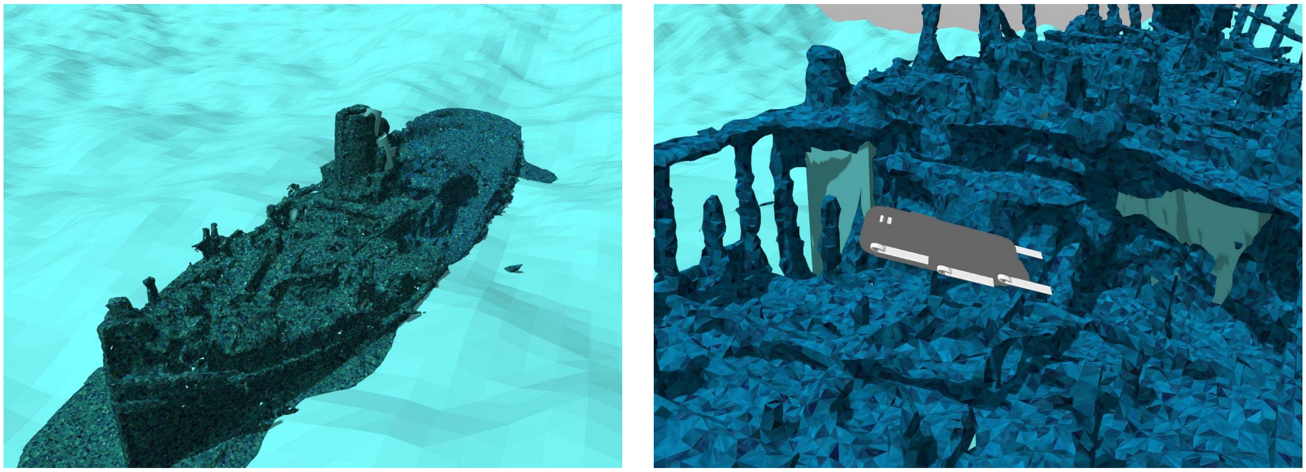
Fig. 4: The labeled data from (a) the gazebo simulation and (b) the underwater video data

To create a vision based navigation system we need to have large dataset of different shipwrecks. We begin with 3D meshes of shipwrecks - the data consists of Gazebo models of shipwrecks provided by the National Oceanic and Atmospheric Administration (NOAA). In addition we have generated test data from the coverage of the Stavronikita shipwreck in Barbados that we have collected by the underwater Aqua2 robot [30] and a GoPro camera. The Aqua2 vehicle is capable of autonomous operations [31] up to a depth of 30 meters. A diver was asked to label data based on the action that they would take if they were to perform coverage around a shipwreck. The possible values that diver selects are the directions in a 2D image - the label window is illustrated in Figure 4. In addition to this label we also use information about the previous action to make better decision on the direction - instead of continuing to circumnavigate the ship the diver might turn back and cover the same line. The labeled data is fed to an 18 layer residual network with similar architecture to the one proposed by Manderson et al. [28] (see Figure 3).This network operates on each frame of the incoming video, classifying each image into one of a possible 49 classes. Each of these classes consists of a yaw/pitch command comprised of two integers from -3 to 3. The predicted class is then used as an input command to the Aqua robot. In training, the network used a batch size of 32 and a dropout rate of 0.2 over 2048 epochs. A stochastic gradient descent method optimized network with a learning rate of 0.01 and a categorical cross entropy loss function. These variables were tuned until the expected behavior could be observed. The output of the system are direction commands that are converted to the yaw, pitch and roll commands to control the Aqua2 robot.

IV. Experimental Results

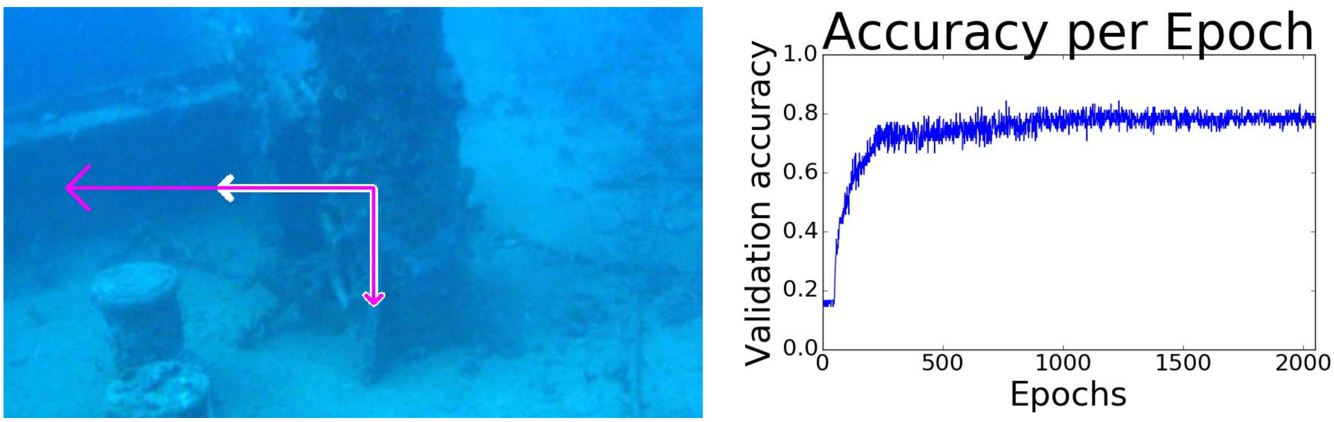
The experiments were performed using the Aqua2 simulator in Gazebo. It emulates the real dynamics of an underwater environment and allows control of the robot. The Aqua2 robot used in simulation uses the motion from six flippers, each independently actuated by an electric motor, to swim. It has 6 degrees of freedom, of which five are controllable. The robot's primary sensing modality is vision. It is equipped with three iDS USB 3.0 UEye cameras: two facing forward and one in the back. The front-facing cameras are used for navigation and data collection.

The test results on training data showed about 80% accuracy on prediction of the direction. As it can be seen from the Accuracy per Epoch plot (Figure 6) the model is converging after less than 300 epochs. In addition studying the samples on which results are producing error it turned out that the direction error is very small. The overall training data consists



(a) (b)

Fig. 5: (a) Gazebo Model of a Schipwreck used for training, (b) AQUA robot navigating over shipwreck in Gazebo



(a) (b)

Fig. 6: (a) The wrong prediction data sample; (b) The accuracy per epoch plot of the proposed method.

of 20,000 data images extracted from three models of shipwrecks. The test data and cross validation data comprise each the 10 percentage of the total data, with no overlaps.

The resulting predictions of direction changes are used to control the robot. A sample execution of controller in Gazebo proves the feasibility of the proposed concept that robot will be able to navigate similar tot he diver around shipwreck. Qualitative results also show that robot is able to get back to the shipwreck when it looses track of it (see Figure 7).

V. Conclusions

With this work we proposed a new strategy for performing navigation underwater with a complete coverage objective. The method is based on the human expertise in performing navigation to collect data from a structure. With reported preliminary results of 80% accuracy achieved from the training on the initial set of simulated and real underwater data, we showed that this approach is feasible and has potential for underwater navigation.

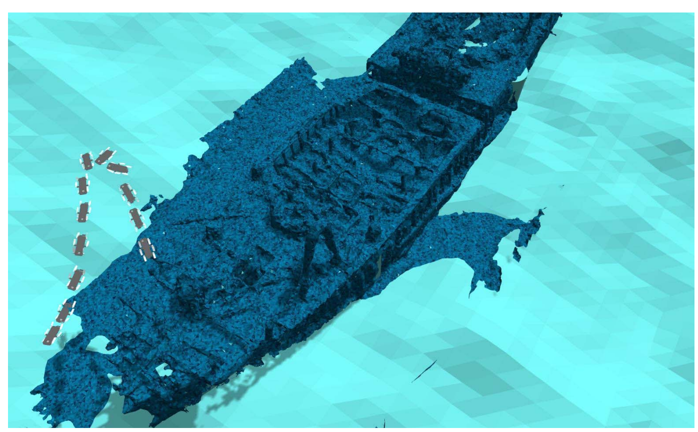


Fig. 7: Portion of a trajectory of robot in simulation produced by prediction based controller

When working in the underwater domain we are limited by the technical constraints of the autonomous platform more than

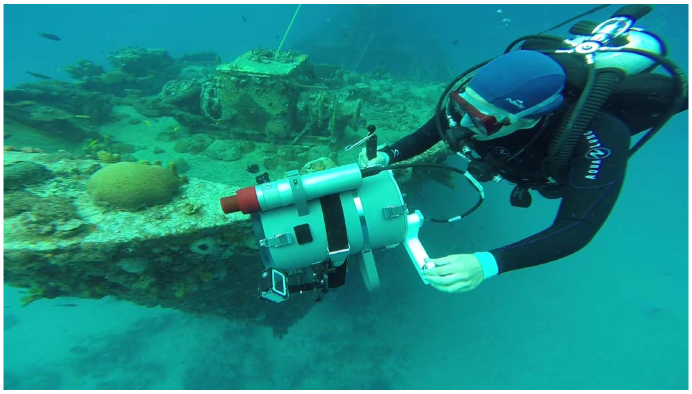


Fig. 8: Data collection around the Pamir shipwreck, Barbados.

on the surface. The constraints of underwater vehicle include but are not limited by the battery life, computational power and cost. In order to be able to successfully execute the online learning-based method, proposed above for 3D coverage, our main experimental platform, the Aqua2 robot, must be upgraded to include Jetson TX2 Module for computations. New experiments and more data have to be collected with Aqua2 to illustrate feasibility of the proposed system. An alternative to AUV data collection is manual collection by divers, using a sensor suite [32], where the human guides the exploration. In addition, a 3D reconstruction of the underwater structure should be generated using the proposed method and state of the art 3D coverage method to show a qualitative differences. And finally, another aspect of interest will be to build a generalized prior map of shipwrecks and use that as a guiding prior information to enhance the coverage in new unknown environment.

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